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# Cost Profiling of Water Infrastructure Projects

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## Cost Profiling of Water Infrastructure Projects

**Abstract:** The expected final budgeted costs of infrastructure assets are often exceeded during project delivery. Being able to determine the likelihood of changes to the final budget can enable clients to implement strategies to manage and control costs during construction. To understand the changing nature of costs, the cost profiles of 1,093 water infrastructure projects that were delivered by a water utility company are examined. Cost overruns were experienced in 656 projects. Only 1 project was delivered on budget with the remaining 436 being completed under the 'Final Budget Approval'. A mean cost overrun and underrun of +19.97% and -32%, were found, respectively. The 'best fit' distribution for cost overruns and underruns for determining their probability of occurrence were calculated. The research moves beyond examining the cost performance of heterogeneous datasets that have dominated previous studies to the use of a homogeneous sample, which enables more reliable contingency forecasts to be determined.

**Keywords:** Cost overrun/underrun, contingency, distribution fitting, risk management, water infrastructure

## Introduction

Water authorities are responsible for constructing, managing, maintaining, and operating a portfolio of assets. Projects that are undertaken will usually be prioritized according to their strategic importance, relative and opportunity cost and the immediate needs of the communities they will serve. In the United Kingdom (UK), £2.3 billion was invested in water infrastructures projects between 2013 and the third quarter of 2014 alone (Office of National Statistics, 2014). Looking ahead, the Scottish Government, for example, will invest £3.5 billion in a strategic program between 2015 and 2021 to improve water mains and treatments works and to deliver solutions to around 400 external sewer programs addressing problems associated with flooding and water quality (Scottish Government, 2014a). The program is estimated to create approximately 5,000 construction jobs and have a significant economic multiplier effect throughout the Scottish economy. This investment in new capital expenditure (CAPEX) is a significant increase from the Government's £1.8 billion 'Quality and Standards II' investment program, which ended in 2014 (Scottish Government, 2014b).

It has been observed that the CAPEX of water infrastructure projects routinely overrun their initial cost estimates leaving clients, financiers, contractors and the public dissatisfied (Ahiaga-Dagbui and Smith, 2012; Ahiaga-Dagbui and Smith, 2014a; Baccarini and Love, 2014). This is not an unusual situation for infrastructure projects in their entirety, as it has been observed that on average, 48% fail to meet their baseline time, cost and quality objectives (Caravel Group, 2013). However, if CAPEX overruns, the scope of works on future projects may be reduced to accommodate the increased expenditure that has been incurred. Contractors could face cash flow issues, liquidity and damage to their business image while the public, where the project is funded

by taxpayer's money, have to pay more for a problem that was not their fault. This may also have a knock-on effect on the amount of funds that will be available for maintaining and operating the built facility.

Surprisingly, despite the propensity for water infrastructure projects to experience cost overruns, there has been limited use of advanced data modelling and statistical analysis in the industry to ameliorate decision-making in relation to the management of risk and uncertainty (Baccarini and Love, 2014). Ahiaga-Dagbui and Smith (2014a) have suggested that all too often risks are either ignored or dealt with in a completely arbitrary manner using rules-of-thumb or deterministic percentages. Baccarini and Love (2014) have previously pointed out that the task of risk management or response in most cases is so poorly performed, that far too much risk is passively retained, ultimately resulting in cost escalation during project delivery.

A common probability distribution used by risk analysts who rely on *Monte Carlo* simulation, for example, is the *Normal* (or Gaussian) Distribution (Hubbard, 2009). Such a distribution is used as it appears to 'fit' observed phenomenon from an array of data often found in manufacturing and actuarial science. Moreover, its use is also assumed to apply to *Options Theory* (e.g. Black and Scholes, 1973; Merton, 1973) and *Modern Portfolio Theory* (Markowitz, 1952; 2005). That said, according to Hubbard (2009), the use of normal distribution does not necessarily reflect what actually arises in reality. As the normal distribution is symmetrical and not skewed, the mean is in the middle. Thus, the standard deviation represents a unit of uncertainty around the mean (Hubbard, 2009). Yet, not all datasets are normally distributed and bell-shaped and therefore it is

important for risk analysts to determine the tails of distributions and identify the best fitting distribution to decide appropriate probabilities of occurrence.

In this paper, the statistical characteristics of 1,093 water infrastructure projects delivered by a large public utility company are analyzed to determine their:

- likelihood and size of cost overruns /underruns arising in future projects;
- empirical distribution of the dataset; and
- ‘best fit’ probability density function (PDF) so that the probabilities of overruns or underruns can be determined.

The research presented moves beyond examining the cost performance of heterogeneous datasets that have dominated previous studies (e.g., Flyvbjerg *et al.* 2002; Ansar *et al.*, 2014) to the use of a homogenous sample, which enables more reliable forecasts to be determined. By utilizing a homogeneous dataset provided by a single asset owner, whose procurement processes, contractual conditions, and technology are consistently applied to the delivery of their assets, offers a basis for developing a robust assessment of risk when compared to studies that have focused on deriving data from disparate projects from around the world (e.g., Ansar *et al.*, 2014). The research presented in this paper provides public and private organizations involved in delivering water infrastructure projects with a platform for benchmarking their cost performance and the ability to improve their risk management prior to the commencement of construction, maintenance and operations of their assets.

## **A Review of Cost Performance**

For an asset owner, such as a water authority, managing the cost performance of their portfolio of projects is essential to ensure its competitiveness and survival; this is a critical metric as it quantifies the cost efficiency of the work completed. Cost performance is generally defined as the value of the work completed compared to the actual cost of progress made on the project (Baccarini and Love, 2014). For the asset owner, the ability to reliably predict the final cost of construction and ensure it does not experience an overrun is vital for ensuring the planning and resourcing of other projects or those in the pipeline. Put simply, a cost overrun is defined as the ratio of the actual final costs of the project to the estimate made at *full funds authorization* measured in escalation-adjusted terms (Merrow, 2011). In this instance, an overrun is treated as the margin between the authorized initial project cost and the real final costs incurred after adjusting for expenditures due to escalation terms. Ahiaga-Dagbui and Smith (2014a;b) examined 1,600 water projects in the UK and found an average cost overrun of 16.75% of the ‘Final Approved Budget’. Contrastingly, the Baccarini and Love (2014) study of 228 Australian sewer and water projects revealed a slightly lower mean cost overrun of 13.58%.

## **Overruns**

There has been a considerable amount of research that has focused on examining the nature of cost overruns and how they can have an adverse impact on organizations (e.g. Merewitz, 1973; Jahren and Ashe, 1990; Pickrell, 1992; Hinze *et al.*, 1992; Vidalis and Najafi, 2002; Gritza and Labi, 2008; Ahiaga-Dagbui and Smith, 2012; Ahiaga-Dagbui and Smith, 2014a,b; Love *et al.*, 2015a,b). According to Ahiaga-Dagbui (2014) two predominant schools of thought have emerged from the on-going discourse regarding the sources of overruns: (1) ‘Evolution Theorists’, who suggest that

overruns are the result of changes in scope and definition between inception stage and eventual project completion (e.g., Odeyinka *et al.*, 2012; Bhargava *et al.*, 2010; Anastasopoulos *et al.*, 2014); (2) ‘Psycho Strategists’ (i.e. a combination of psychological contributors and business strategy) attribute overruns to deception, planning fallacy and unjustifiable optimism in the setting of initial cost targets (e.g., Flyvbjerg *et al.*, 2002; Ansar *et al.*, 2014).

There has been a widespread campaign for using the ‘outside view’ advocated by Flyvbjerg *et al.* (2002), which is founded on the notion that *optimism bias* (i.e. the underestimation of risks and overestimation of benefits) and *strategic misrepresentation* (i.e. deception) as they are perceived to be the key constituents that contribute to cost overruns in projects. While there are grounds for this argument put forward, the evidence presented lacks credibility and is unscientific; no evidence of any causal relationship is provided (Love *et al.*, 2012; Love *et al.*, 2015a,b). Osland and Strand (2010) have been particularly critical of the ‘outside’ view purported in Flyvbjerg *et al.* (2002), as they conclude that they applied the *logic of suspicion* in their claim that inaccurate cost forecasting is a result of optimism bias and strategic misrepresentation.

In support of an ‘inside view’, which focuses on specific planned actions, Love *et al.* (2012) suggest that cost overruns arise as a result of a series of pathogenic influences, which lay dormant within the project system. However, before such influences become apparent, participants often remain unaware of the impact that particular decisions, practices and procedures can have on project performance. Accordingly, this school of thought is widely supported by authors such as Odeck (2004), Aibinu and Pasco (2008) and Odeyinka *et al.* (2012). Essentially, Love *et al.* (2012) and Ahiaga-Dagbui and Smith (2014a) imply from their research that overruns are not really a case



of ‘projects not going according to plan (budget)’, but ‘plans not going according to project’. That is, the realities of project delivery, in terms of latent conditions, technical designs, risk profiles or contingencies, do not always reflect expectations at the planning stage.

While Love *et al.* (2012) have been critical of the ‘outside view’ promulgated by Flyvbjerg (2002), in recent works, Love *et al.* (2015b) acknowledge that political, economic, psychological and managerial factors may generate the pathogenic influences that can arise in projects. Subsequently, Ahiaga-Dagbui (2014) and Love *et al.* (2015b) have advocated for a ‘balanced approach’ that focuses on how process and technological innovations can be used to improve the cost performance of infrastructure projects. Fundamentally, understanding ‘why’ and ‘how’ projects overrun, from both ‘outside’ and ‘inside’ perspectives, is pivotal to reducing their impact and occurrence.

The above discourse provides a brief contextual backdrop for understanding the nature of cost overruns. A detailed review of the mainstream arguments on the causes of cost overruns can be found in Ahiaga-Dagbui and Smith (2014a,b) and Love *et al.* (2015a,b). A recurring theme that emerges from previous studies is the reference point (i.e. initial budget or contract award) from where a cost overrun is determined (Love *et al.*, 2013). The reference point used influences the size of the cost overrun that is reported. Another emergent issue relates to the size of a project; smaller projects experience greater percentage cost increases than larger ones (e.g. Odeck, 2004a,b). This suggests that larger projects may be better managed and that longer completion times provide an opportunity to make adjustments to facilitate cost control (Jahren and Ashe 1990; Odeck, 2004). Despite the accumulated wealth of knowledge that has been acquired about cost

overruns, their prediction remains a pervasive challenge. This is due to the limited and heterogeneous sample sizes that have previously been used to determine their statistical characteristics and distribution profiles. The result, thereof, is inappropriate risk management strategies and unrealistic levels of construction cost contingency (Baccarini and Love, 2014).

## **Research Method**

The industry partner that provided the dataset for this research is a utility company in the UK that provides water and sewerage services to over 2.5 million households and 150,000 business customers. The collaborating organization typically has three stages of estimation before inviting bids from contractors – known as the third-stage estimate (i.e. Gate Three). This is usually based on about 50-60% completed scope design and is used for evaluation of tenders after which detailed design is carried out by the selected contractor in a sort of design and build contract framework.

The data collection process involved an initial shadowing of the tendering and estimation procedure within the organization. The researchers were allowed to be *quasi*-members of the tendering team of the company on some of its projects to observe how the estimates were produced. It was also an opportunity to gain a first-hand understanding of how the data to be used in the analysis was generated and what different variables meant. The initial dataset used contained 1,600 projects. The scope of these projects varied from construction of major water treatment plants to minor repairs and upgrade. After the removal of cases with significant missing data and input errors, the final dataset that was used for the analysis in this paper contained 1,093 water infrastructure projects, completed between 2002 to 2012. Cost indexing was not considered as only the percentage cost overrun/underrun as a proportion of the value at contract award was examined.

To improve risk management in the delivery of future infrastructure projects and determine the appropriate construction contingency, the statistical characteristics of those that had been completed were examined and their cost profiles modeled (Baccarini and Love, 2014). In determining the statistical characteristics of the sample and probability of cost overrun/underruns being incurred, the ‘cost profiling’ method suggested by Baccarini and Love (2014) is adopted and presented below. This method is replicated so the results of the study can be compared to the cost profiling of water infrastructure projects elsewhere. Moreover, profiling projects of the same type provide the basis for developing the much needed scientific basis for developing standard cost profiles needed for estimating their performance. The theory is somewhat akin to *Prospect Theory*, which is a method of predicting the future, through looking at similar past situations and their outcomes (Kahneman and Tversky, 1979). Flyvbjerg and Cowi (2004) build on this work and refer to it as *Reference Class Forecasting* (RCF). The key point of departure in this research, however, resides within the way in which the ‘best fit’ distribution is determined and computed; a *Normal* distribution is not assumed.

Ascertaining the ‘best fit’ probability distribution lies at the heart of cost profiling of infrastructure projects (Love *et al.*, 2013; Baccarini and Love, 2014; Love *et al.*, 2015a,b). Fundamentally, probability distributions can be viewed as a tool for dealing with uncertainty: they can be used to perform specific calculations, and therefore results can improve the effectiveness of decision-making. If an inappropriate distribution is selected, which is misaligned with the nature of the data used for the modelling, subsequent calculations will, as a result, be questionable. The use of incorrect probability distributions may also have other serious consequences such as an inability to complete the projects altogether. Clients may also have to secure additional funding or suffer

reputational detriments. In addition, financiers may have to suffer the consequences of their investment not returning profits for a longer period, or not at all. Distribution fitting enables the development and derivation of valid models of random processes and is therefore used to mitigate potential cost and schedule overruns that can arise in infrastructure projects, invariably due to invalid model selection.

An example where RCF was applied and an inappropriate distribution used was the Edinburgh Tram and Airport Link project in the UK (Love *et al.*, 2013). The project was originally estimated to cost £320 million, which included a risk contingency based-estimate (Auditor General for Scotland and Accounts Commission, 2011). Taking all the available distributional information into account, by considering a reference class of comparable rail projects (e.g. London Docklands Light Rail), the reference class estimated an 80<sup>th</sup> percentile value of £400 million. The project was completed three years late in the summer of 2014 at a reported *construction cost* of £776 million (City of Edinburgh Council, 2014). Considering claims and contractual disputes, which partly occurred due to errors and omissions in contract documentation, a revised estimated final cost of over £1 billion has been forecasted, including £228 million in interest payments on a 30-year loan to cover the funding shortfall (BBC, 2011). As noted above, RCF has several limitations and the relative effectiveness of Risk-Based Estimation methods developed has yet to be adequately demonstrated (Liu and Napier, 2009). Thus, Love *et al.* (2015) have suggested that to improve the reliability of risks in the form of a contingency estimate at ‘Final Approved Budget’, the empirical distributions of cost overruns need to be examined to determine their ‘best fit’ probability so that an appropriate construction contingency sum can be determined. In this case, by determining the

‘best fit’ probability distribution for the homogenous sample provided, the likelihood of a portfolio of projects meeting their desired cost performance can be attained.

### **Procedure**

Descriptive statistics such as the mean (M), standard deviation (SD), skewness, kurtosis and inter-quartile values were calculated for cost data for 1,093 water infrastructure projects delivered in the UK. A cost overrun/underrun is determined by the difference between the ‘Final Approved Budget’ (i.e. contract award) and ‘Final Construction Cost’. A one-way analysis of the variance (ANOVA) of cost profile (i.e. overruns and underruns) and correlations were undertaken to examine differences between the size (i.e. in terms of their total approved budget), location (i.e. North, South, East and West of the region), project type (i.e. general, waste water and water) and scope (i.e. upgrade, new-build or refurbishment). To identify where any differences may have existed within a sample, a Tukey’s honest significant difference (HSD) post-hoc test was used (Tukey, 1949).

Noteworthy, ‘general projects’ are ancillary works and include upgrades and health and safety or environmental compliance or minor repair works. ‘Waste water projects’ refer to the construction and maintenance of pipework systems and other physical infrastructure required for transporting or treating effluent from home and industries through a combined or sanitary sewer. ‘Water projects’ relate to infrastructure works that collect, treat, store and distribute drinking water. Project schedule was not included in the analysis as there is a proclivity for it to be contained within a construction program as ‘float’ or ‘slack’. This point has been identified in the research produced by Baccarini and Love (2014) when they sought to examine the nature of construction

cost contingency and overruns in water infrastructure projects from a homogenous sample in Western Australia.

The PDF and Cumulative Density Functions (CDF) for the difference between the ‘Final Approved Budget’ and ‘Final Cost’ were computed using the software EasyFit 5 and the probability of an overrun/underrun being experienced for future projects were identified for this client organization.

A PDF for a continuous random variable,  $X$ , between the interval  $[a, b]$ , can be expressed as the integral function:

$$\int_a^b f(x)dx = P(a \leq X \leq b) \quad [\text{Eq.1}]$$

A CDF was also produced. For theoretical continuous distributions, the CDF is expressed as a curve and denoted by:

$$F(x) = \int_{-\infty}^x f(t)dt \quad [\text{Eq.2}]$$

The empirical CDF, which is displayed as a stepped discontinuous line and dependent on the number of bins ( $n$ ), is represented by:

$$F_n(x) = \frac{1}{n} \cdot [\text{Number of observations} \leq x] \quad [\text{Eq.3}]$$

The PDF, CDF and distribution parameters such as  $(\alpha, \beta, \gamma, \mu, k, m, \sigma, \xi)$  were examined for continuous distributions such as *Beta*, *Burr*, *Cauchy*, *Error*, *Gumbel Max/Min*, *Johnson SB*,

*Normal* and *Wakeby* using their respective estimation methods of Maximum Likelihood Estimates.

Then, using the *StatAssist* function within *EasyFit 5.5*, the ‘best fit’ distribution was then determined using the following ‘Goodness of Fit’ tests, which measures the compatibility of a random sample with the following theoretical probability distributions:

- *Kolmogorov-Smirnov statistic (D)*: Based on the largest vertical difference between the theoretical and empirical CDF:

$$D = \max_{1 \leq i \leq n} \left[ F(x_i) - \frac{i-1}{n}, \frac{i}{n} - F(x_i) \right] \quad [\text{Eq.4}]$$

- *Anderson-Darling statistic (A<sup>2</sup>)*: A general test to compare the fit of an observed CDF to an expected CDF. The test provides more weight to distributions tails than the *Kolmogorov-Smirnov* test. The Anderson-Darling statistic is defined as:

$$A^2 = -n - \frac{1}{n} \sum_{i=1}^n (2i-1) \cdot [\ln F(x_i) + \ln(1 - F(x_{n-i+1}))] \quad [\text{Eq.5}]$$

- *Chi-squared statistic (χ<sup>2</sup>)*: Determines if a sample comes from a population with a specific distribution. The Chi-squared statistic is defined as:

$$\chi^2 = \sum_{i=1}^k \frac{(O_i - E_i)^2}{E_i} \quad [\text{Eq.6}]$$

where  $k$  is a positive integer that specifies the number of degrees of freedom;  $O_i$  is the observed frequency for bin  $i$ ; and  $E_i$  is the expected frequency bin  $i$  calculated by:

$$E_i = F(x_2) - F(x_1) \quad [\text{Eq.7}]$$

Here,  $F$  is the CDF of the probability distribution being tested, and  $x_1, x_2$  are the limits for the bin  $i$ .

The above ‘Goodness of Fit’ tests were used to test the null ( $H_0$ ) and alternative hypotheses ( $H_1$ ) that the datasets:  $H_0$  - follows the specified distribution; and  $H_1$  - does not follow the specified distribution. The hypothesis regarding the distributional form is rejected at the chosen significance level ( $\alpha$ ) if the statistic  $D, A^2, \chi^2$  is greater than the critical value. For the purposes of this research, a 0.05 significance level was used to evaluate the null hypothesis. The  $p$ -value, in contrast to fixed  $\alpha$  values, is calculated based on the test statistic and denotes the threshold value of significance level in the sense that  $H_0$  will be accepted for all values of  $\alpha$  less than the  $p$ -value. Once the ‘best fit’ distribution was identified the probabilities for determining a cost overrun/underrun were calculated using the CDF. To simulate the samples’ randomness and derive cost overrun and underrun probabilities, a *Mersenne Twister*, which is a pseudo-random number generating algorithm, was used to generate a sequence of numbers that approximated the sample to 5,000 (Matsumoto and Nishimura, 1998).

## Results

Of the 1,093 projects provided by the water authority, it was revealed that 656 projects experienced a cost overrun, one was delivered on budget and 436 experienced an underrun (Table 1). In Figure 1, the ‘cost performance’ of the entire sample in relation to cost overruns and underruns are displayed using a Logarithmic scale. In this instance, ‘cost performance’ is the ability of an organization to ensure its project portfolio for a given period does not exceed the ‘Final Approved



Budget'. When examining the entire sample the Mean (M) and Standard Deviation (SD) were found to be -0.77% and 41.52% respectively. Further analysis of the sample by project size revealed that the M and SD varied significantly, as displayed in Figures 2 and 3. A one-way ANOVA was used to test the 'cost performance' for the sample per annum for differences. Notably, for any given year a project was undertaken, Levene's test of homogeneity of the variances was found not to be violated ( $p < 0.5$ ), which indicated the population variances for each group of project size were equal.

Cost overruns and underruns were extracted from the main sample to obtain an informed understanding of their characteristics. In fact, the statistical characteristics of cost underruns have been generally ignored in the normative literature. Thus, it was considered pertinent in this instance to promulgate their statistical characteristics. Considering the distribution of the samples presented in Figure 2 and 3, is there a difference between project size and cost overruns and underruns? A one-way ANOVA was used in this instance to test for differences. In the case of overruns, Levene's test of homogeneity of the variances was found to be violated ( $p < 0.5$ ), which indicated the population variances for each group of project size were not equal. The ANOVA revealed significant differences between the project size classifications,  $F(5, 651) = 8.173$  ( $p < 0.5$ ). The results of Tukey's HSD post hoc test indicated that difference existed between projects less than £10 million and those with a 'Final Approved Budget' exceeding this value. In examining the association between cost overruns and project, a Pearson's correlation ( $r$ ) was computed (Table 2). The correlation analysis revealed that cost overruns and project size were significantly related ( $p < 0.01$ ). Thus, smaller projects in this sample were prone to higher cost overruns than larger ones. Contrastingly, Levene's test of homogeneity of the variances were found to be violated ( $p < 0.5$ )

for cost underruns, which indicated the population variances for each group of project size were equal, as the ANOVA revealed,  $F(5, 430) = 1.541$  ( $p < 0.5$ ).

Other than project size, previous research has identified that ‘location’, ‘purpose’, ‘partner’ and ‘scope’ do not significantly vary with water infrastructure projects (Baccarini and Love, 2014). However, the sample size in this research was considerably larger than previous studies (e.g. Baccarini and Love, 2014) and therefore differences between these variables were examined. As a result, the following was observed:

- *Partner* (Division A,  $N=601$ ,  $M=30.52\%$ ,  $SD=25.11\%$ ; Division B,  $N=21$ ,  $M = 11.88\%$ ,  $SD=23.1\%$ ; Division C,  $N=471$ ,  $M=14.31\%$ ,  $SD=19.78\%$ );
- *Location* (North,  $N=191$ ,  $M=15.61\%$ ,  $SD=20.42\%$ ; South,  $N=375$ ,  $M=25.64\%$ ,  $SD=26.39\%$ ; East  $N=191$ ,  $M=21.71\%$ ,  $SD=24.60$ ; West,  $N=275$ ,  $M=15.17\%$ ,  $SD=17.63\%$ );
- *Purpose* (General,  $N=44$ ,  $M =27.22\%$ ,  $SD=17.03\%$ ; Waste water  $N=491$ ,  $M=16.68$ ,  $SD=21.31$ ; Water  $N=558$ ,  $M=23.19$ ,  $SD=24.87$ ); and
- *Scope* (New build,  $N=1$ ,  $M=10.57\%$ ; Refurbishment,  $N=1$ ,  $M=1.01\%$ , Upgrade,  $N=1093$ ,  $M=20.2, 23.23\%$ ).

Note, one replacement project was also undertaken, but this was delivered in accordance with the ‘Final Approved Budget’.

A one-way ANOVA was undertaken to determine if significant differences existed between the aforementioned variables and cost overruns. Levene’s test of homogeneity of the variances was found not to be violated for project scope ( $p < 0.5$ ), which indicated the population variances for

each group of project size were equal. For the following variables, however, Levene's test of homogeneity of the variances was found to be violated ( $p < 0.5$ ), which indicated the population variances within their group project size were not equal:

- *Location*: The ANOVA revealed significant differences between the 'location' and the mean cost overrun experienced  $F(3,653) = 8.952, p < 0.05$ . The results of Tukey's HSD post hoc test indicated that difference existed between projects delivered between 'general' and 'waste' projects ( $p < 0.5$ );
- *Purpose*: The ANOVA revealed significant differences between the 'purpose' and the mean cost overrun experienced  $F(2,654) = 6.485, p < 0.05$ . The results of Tukey's HSD post-hoc test indicated that difference existed between projects delivered between 'north' and 'south' of the region ( $p < 0.5$ ); and
- *Partner*: The ANOVA revealed significant differences between the 'purpose' and the mean cost overrun experienced  $F(2,654) = 41.320, p < 0.05$ . The results of Tukey's HSD post-hoc test indicated that difference existed between 'Division A' and 'C' of the client's organization that were charged with delivering projects ( $p < 0.5$ ).

In the case of cost underruns, the ANOVA analysis revealed that Levene's test of variance for 'location', 'purpose' and 'partner' was found not to be violated ( $p < 0.5$ ), which demonstrated that these variables do not significantly influence the propensity for assets to be delivered under budget. Typically at the beginning of a financial year, a budget for a program of infrastructure works is established. Stringent budgetary controls are invariably be put in place to ensure that the budget for these works are not be exceeded. In addition, projects are be prioritized in accordance with pre-

defined criteria. If prioritized projects begin to experience a cost increase, then the scope of other projects may be reduced or only part of the works completed with the remainder, perhaps, being allocated to the next financial year.

For the dataset presented herein, the ‘Approved Final Budget’ for projects  $\underline{M}=\pounds1,259,176$ ;  $\underline{SD}=\pounds6,117,125$ , and for the ‘Final Construction Cost’  $\underline{M}=\pounds1,376,055$ ;  $\underline{SD}=\pounds5,891,590$ . A *t*-test was undertaken to examine if there was a significant difference between the ‘Approved Final Budget’ and ‘Final Construction Cost’. At the 95% confidence interval, no significant difference was found. Thus, in the context of cost performance for this sample of 1,093 projects, it concluded that the ‘Approved Final Budget’ was a reliable estimate of the ‘Final Construction Cost’.

### **Cost Performance**

The ‘best fit’ probability distribution for ‘cost performance’ was examined using the ‘Goodness of Fit’ tests: Kolmogorov-Smirnov (*D*), Anderson-Darling ( $A^2$ ) and Chi-square ( $\chi^2$ ). The results of the ‘Goodness of Fit’ tests revealed that an unbounded *Cauchy* distribution with parameters  $\sigma = 4.31$ ,  $\mu = 3.47$  was identified as the ‘best fit’ solution for examining the cost performance of the sample. The Kolmogorov-Smirnov test revealed a *D* statistic of 0.03559 with a *P*-value of 0.12241. The Anderson-Darling statistic  $A^2$  was revealed to be 3.8536 and Chi-squared statistic ( $\chi^2$ ) 72.585 with a *p*-value of 1.4013E-11. The Kolmogorov-Smirnov test accepted the  $H_0$  for the sample distribution’s ‘best fit’ at the critical nominated  $\alpha$  values (Table 3), though this was not the case for the Anderson-Darling test. The PDF and CDF for the *Cauchy* distribution are presented in Figures 5 and 6.

An unbounded *Cauchy* distribution has a positive excess kurtosis and is leptokurtic. It also has an acute *peak* around the mean (that is, a lower probability than a normally distributed variable of values near the mean). With this distribution,  $\sigma$  is the continuous scale parameter ( $\sigma > 0$ ) and  $\mu$  continuous location parameter. The domain for this distribution is expressed as  $-\infty < x < +\infty$ . The probabilities for cost performance' were then determined using the *Cauchy* PDF function which is defined as:

$$F(x) = \left( \pi \sigma \left( 1 + \left( \frac{x-\mu}{\sigma} \right)^2 \right) \right)^{-1} \quad [\text{Eq.8}]$$

The CDF is expressed as:

$$F(x) = \frac{1}{\pi} \arctan \left( \frac{x-\mu}{\sigma} \right) + 0.5 \quad [\text{Eq.9}]$$

Using the *Cauchy* PDF the probability of obtaining a cost performance  $< \underline{\mathbf{M}} - 0.77\%$  of the 'Final Approved Budget' was 41%. In addition, the probability of obtaining between 5 and 10% increase in CAPEX is 12%. Notably, the probability of attaining  $< 5\%$  increase in CAPEX is 57%, and  $> 10\%$  was 31%.

### **Cost Overruns**

The results of the 'Goodness of Fit' tests revealed that a *Johnson S<sub>B</sub>* distribution with parameters  $\gamma = 1.1057$ ,  $\delta = 0.48993$ ,  $\lambda = 97.649$ , and  $\xi = 0.45619$  was identified as the 'best fit' solution for examining the 'cost overruns'. Notably,  $\gamma$  and  $\delta$  ( $\delta > 0$ ) are a continuous shape parameters,  $\lambda$  continuous scale parameter ( $\lambda > 0$ ) and  $\xi$  a continuous location parameter. The domain for this distribution is expressed as  $\xi \leq x \leq \xi + \lambda$ . The Kolmogorov-Smirnov test revealed a *D* statistic of 0.04362 with a *P*-value of 0.15928 the Anderson-Darling statistic  $A^2$  was revealed

to be 48.387. The ‘Goodness of Fit’ tests were accepted the  $H_0$  for the sample distribution’s ‘best fit’ at the critical nominated  $\alpha$  values for Anderson-Darling test and at  $\alpha=0.2$  for the Kolmogorov-Smirnov test (Table 3). The PDF and CDF for the *Johnson  $S_B$*  are presented in Figures 7 and 8.

The *Johnson  $S_B$*  is a bounded distribution (alternatively known as the four-parameter lognormal model) typically used as a candidate for variates constrained by extreme values (Flynn, 2006). It is part of a system of distributions, developed by Johnson (1949), which are generated by methods of translation on a standard normal variate that permits representation over the whole possible region of the plane  $(\beta_1, \beta_2)$ , where  $\beta_1$  is the square of the standardized measure of skewness and  $\beta_2$  is the standardized measure of kurtosis. The *Johnson  $S_B$*  has two properties that ensure it is well-suited to represent the cost overruns for this sample of projects:

- (1) lower bound,  $\xi$ , and upper bound,  $\xi + \lambda$ , for the PDF can represent financial constraints that are imposed by the organization due to an annual budget that is established for its portfolio of infrastructure projects. Naturally  $\xi + \lambda$ , would be established at the ‘Approved Final Budget’ depending on the nature of the work to be undertaken and completeness of the engineering design and documentation;
- (2) the shape parameters ( $\gamma$  and  $\delta$ ) allow a considerable amount of flexibility to fit a broad spectrum of distributions (Fonseca *et al.*, 2009). The parameters of the *Johnson  $S_B$*  PDF can be estimated by the percentile method, maximum likelihood, moments and linear and non-linear regression methods (Zhang *et al.*, 2003). The *Johnson  $S_B$*  PDF function is defined as:

$$f(x) = \frac{\delta}{\lambda\sqrt{2\pi z(1-z)}} \exp\left(-\frac{1}{2}\left(\gamma + \delta \ln\left(\frac{z}{1-z}\right)\right)^2\right) \quad [\text{Eq.10}]$$

460 Where  $z \equiv \frac{x-\xi}{\lambda}$ . The CDF is expressed as:

461 
$$f(x) = \Phi \left( \gamma + \delta \ln \left( \frac{z}{1-z} \right) \right) \quad [\text{Eq.11}]$$

462  $\Phi$  is the *Laplace Integral*, which is defined as:

463 
$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_0^x e^{-t^2/2} dt \quad [\text{Eq.12}]$$

464  $t$  is a real number. The probabilities for cost overruns being incurred when underruns are excluded  
465 from the sample are presented in Table 4. The probability of a cost overrun being  $< \underline{M}$  of 19.99%  
466 is 66%. Moreover, the probability of a 50 % cost overrun being  $>$  is 12%.

467

#### 468 **Cost Underruns**

469 Cost underruns formed an integral part of this dataset and thus are analyzed separately to  
470 understand their distribution and the likelihood of their occurrence within the organization's  
471 portfolio of projects. The 'Goodness of Fit' tests: *Kolmogorov-Smirnov and Anderson-Darling*  
472 were undertaken. The results of the 'Goodness of Fit' tests revealed that *Wakeby* distribution  
473 provided the best fit for the dataset. The Kolmogorov-Smirnov test revealed a  $D$ -statistic of  
474 0.02263 with a  $p$ -value of 0.97517 for the sample of 436 water infrastructure projects (Table 3).  
475 The Anderson-Darling statistic  $A^2$  was revealed to be 53.421. The PDF and CDF for the *Wakeby*  
476 distribution are presented in Figures 9 and 10.

477

478 The Wakeby is a form of *Generalized Extreme Value* distribution. The parameters of a *Wakeby*,  
479  $\alpha \beta \gamma \delta \xi$  are all continuous. The domain for this distribution is expressed as  $\xi \leq x$ , if  $\delta \geq$  and  
480  $\gamma > 0$ ,  $\xi \leq x \leq +\alpha/\beta - \gamma/\delta$  if  $\delta < 0$  or  $\gamma = 0$ . The distribution parameters for the range were  $\alpha =$

1936.7,  $\beta = 11.372$ ,  $\gamma = 78.309$ ,  $\delta = -1.6536$ ,  $\xi = -218.09$ . The *Wakeby* distribution is defined by the quantile function (i.e. inverse CDF):

$$x(F) = \xi + \frac{\alpha}{\beta} (1 - (1 - F)^\beta) - \frac{\lambda}{\delta} (1 - (1 - F)^{-\delta}) \quad [\text{Eq.13}]$$

Table 4 presents the probability of cost overruns being experienced. The probability of a cost underrun being  $< \underline{M}$  of -32.0% is 28%. Moreover, the probability of a -50% cost overrun being experienced  $>$  is 81%.

## Discussion

The homogenous dataset of water infrastructure projects delivered by a water authority using a common contractual delivery method has enabled the results that were obtained to be compared to the research reported in Baccarini and Love (2014). In stark contrast to Baccarini and Love (2014), statistical differences in the ‘cost performance’ were found for ‘location’, ‘purpose’ and the body within water authority charged with delivering the respective project within the specified location. As noted above, this may be due to the size of the sample, though the  $\underline{M}$  ‘cost performance’ significantly differed between the studies reported within Baccarini and Love (2014) who reported 5.12% ( $\underline{SD}=25.95$ ) cost increase compared to -0.77% ( $\underline{SD}=41.92$ ) of the ‘Final Approved Budget’ in this study. Bearing in mind the significant differences in the mean and the reported standard deviations, there would naturally be differences between the comparative empirical and ‘best fit’ distributions.

For ‘cost performance’, Baccarini and Love (2014) computed a *Generalized Logistic* distribution, which is similar to a *Normal* distribution but possesses a higher kurtosis value, due to extreme



values. This type of distribution is unbounded (i.e. has a range of  $-\infty < x < +\infty$ ) like the *Cauchy* that was revealed for ‘cost performance’ in this study. Baccarini and Love (2014) did not differentiate between cost overruns and underruns in their analysis and therefore the distribution they suggested does not actually reflect the propensity for cost overruns to arise, but simply to the sample at large. The research presented in this paper suggests that cost overruns and underruns need to be explicitly separated and analyzed independently so as to better determine their likelihood of occurrence for improved risk management. From previous studies undertaken, it would appear that cost overruns and underruns have been combined and juxtaposed with heterogeneous samples, which has distorted their predictions (e.g. Flyvbjerg and Cowi, 2004).

### **Cost Overruns**

For cost overruns, the *Johnson S<sub>B</sub>* offers an approach for estimating extreme values and this is particularly useful when undertaking risks assessments at ‘Final Approved Budget’, considering what has previously transpired within the sample and reported in the findings of Baccarini and Love (2014). The quantile and ‘method of moments’ (i.e. estimation of population parameters) employ analytic expressions for the moments and their numerical integration is therefore not required (Johnson *et al.*, 1994). The *Johnson S<sub>B</sub>* is a flexible four-parameter probability model that soundly characterizes variates bound by extreme values, or simply expressed as ratios. Rather than being unbounded like those reported in previous cost overrun studies (e.g. Love *et al.*, 2013), this distribution is bounded, as water authorities have limited budgets and therefore while some projects may be of the utmost importance, their scope can be changed to limit the excessive amount of overrun that is incurred.

There are challenges with using this distribution due to its mathematical complexity and the lack of effective maximum likelihood methods when three or four parameters are required to be estimated (Flynn, 2005). However, the results presented are considered to be a reasonable approximation for the data that was modelled and with larger datasets the estimation of parameters will, no doubt, improve over time. When the moments of the *Johnson S<sub>B</sub>* are hard to obtain, then the parameters can also be difficult to determine for the purposes of risk analysis. Hence, a three-dimensional *Levenberg-Marquardt* algorithm may be applied in this instance to solve the parameters (Nocedal and Wright, 2005). The *Leven-Marquardt* is an alternative to the Gauss-Newton method of finding the minimum of a function  $F(x)$  that is the sum of squares of nonlinear functions and is expressed as:

$$F(x) = \frac{1}{2} \sum_{i=1}^m [f_i(x)]^2 \quad [\text{Eq.14}]$$

$m$  is a set of empirical datum pairs  $(x_i, y_i)$  of the independent and dependent variables. Let the Jacobian of  $f_i(x)$  be denoted  $J_i(x)$ , then the *Leven-Marquardt* method searches in the direction given by  $\mathbf{p}$  to the equations:

$$\left( J_k^T J_k + \lambda_k \mathbf{I} \right)_{pk} = -J_k^T f_k \quad [\text{Eq.15}]$$

where  $\lambda_k$  are non-negative scalar and  $\mathbf{I}$  is the identity matrix. The method has the nice property that, for some scalar  $\Delta$  related to  $\lambda_k$ , the vector  $p_k$  is the solution of the constrained sub-problem of minimizing  $\|J_k p + f_k\|_2^2 / 2$  subject to  $\|p\|_2 \leq \Delta$  (Gill *et al.*, 1981;p.136).

## **Cost Underruns**

Cost overruns have been regularly equated with the presence of *optimism bias*, yet the opposite is *pessimism bias*, which has remained absent from the construction and engineering literature (Love *et al.*, 2015). Pessimism bias is the tendency to exaggerate the likelihood that negative things will occur. In this case, this may have arisen if a series of projects were overrunning and future works that need to be undertaken by the asset owner were subjected to drastic changes in their scope in order to control CAPEX for the portfolio. It can be seen that significant reductions from the ‘Final Approved Budget’ and ‘Final Construction Cost’ were evident in this particular sample of projects. This view is simply conjectured, as no direct evidence was made available to the researchers. However, it is a worthy area for future investigation considering the lack of empirical work in this domain. Thus, it is suggested that ‘cost underruns’ are just as important to examine as ‘cost overruns’, especially for asset owners who are managing a series of projects and trying to ‘balance’ their yearly financial budgets.

## **Research Limitations**

The research presented in this paper has focused on profiling cost overruns as well as underruns for an asset owner who supplies water infrastructure within the UK. The dataset was homogenous and therefore the probability distributions developed may not be generalizable. In addition, the research did not focus on the causes of cost overruns or underruns. While a causal explanation provides a context and assists with understanding the problem at hand, the issue is complex.

Determining the cause of an overrun is fraught with ambiguity as researchers invariably sieve through the available evidence and look for fragments of information that seem to point to a common cause in developing *a priori* explanation. Moreover, details that are relevant to explaining

the actions and behaviors of people can be overlooked and the information collated is meaningless outside the context where it originated. Invariably the pieces of information obtained are combined with those of a similar nature, though it may have its own context and *raison d'etre*. Context is therefore needed to understand why projects were subjected to both cost overruns and underruns and it is an issue that will be examined in future research using situational sense-making and probabilistic theory. The acquisition of such understanding will then provide the basis for the establishment of reliable benchmarks and probabilities.

## **Conclusions**

Asset owners who regularly procure, maintain and operate infrastructure are required to manage the portfolio of projects that they undertake to ensure annual financial budgets meet their pre-defined objectives. Yet, there has been a tendency to use deterministic approaches to manage risks, particularly the construction contingency, which has not been able to accommodate the uncertainty that may arise during on-site operations.

Using a dataset for a homogenous asset class of water infrastructure projects provided by a large public utility company in the UK, a profile of their cost performance was examined and the probability of overruns and underruns occurring was determined. The analysis revealed that the mean 'cost performance' of projects was -0.77% of the 'Final Approved Budget'; that is, on average underruns were experienced. A *Cauchy* distribution was found to provide the 'best fit' distribution for cost performance. The combining of cost overruns and underruns datasets to determine the likelihood of their occurrence can be unreliable as it does not provide an assessment of the maximum-likelihood estimation required to produce estimates for the parameters of the 'best

fit' model for developing a realistic construction cost contingency. By separating the dataset, the mean cost overrun was found to be 19.97% of 'Final Budget Approval', and with a 'best fit' distribution being a *Johnson S<sub>B</sub>*. However, a mean underrun of -32% of 'Final Approved Budget' was obtained with a *Wakeby* 'best fit' distribution. The probability distributions that were established were then used to calculate the likelihood of their occurrence at various intervals. Such probabilities provide decision-makers with a reliable basis to determine an appropriate contingency level and therefore make a positive contribution to improving the management of risk.

Further research is, however, required to test the reliability of the probability distributions with larger homogenous samples of projects rather than those of a heterogeneous nature. This will then enable the development of a decision-support system that can be used for managing risk within an asset owners' project portfolio. Such a decision-support system would be integrated into the asset owners estimating, and strategic planning and procurement process enabling the practical applications of results presented in this paper.

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Table 1. Descriptive statistics for cost performance, overrun and underruns

<b>Statistic</b>	<b>Cost Performance(£) (N=1093)</b>	<b>Cost Overruns (£) (N=657)</b>	<b>Cost Underruns (£) (N=436)</b>
Range (%)	331.43	98.74	232.65
Mean (%)	-0.77	19.973	-32.044
Variance	1724.2	538.85	1885.4
Std. Deviation	41.52	23.213	43.42
Coef. of Variation	-53.45	1.1622	-1.35
Std. Error	1.25	0.90563	2.07
Skewness	-1.65	1.4633	-2.22
Excess Kurtosis	6.21	1.243	4.74
Min (%)	-232.69	0	-232.69
5%	-72.89	0.828	-140.7
10%	-37.46	1.58	-85.84
25% (Q1)	-9.62	3.58	-37.49
50% (Median)	2.27	8.95	-15.79
75% (Q3)	13.08	29.59	-5.09
90%	45.85	56.884	-1.62
95%	62.63	70.008	-0.70
Max (%)	98.74	98.74	-0.03

Table 2. Correlations between key variables

Variable	Project Size	Location	Purpose	Cost Underrun	Cost Overrun	Cost Performance	Scope	Partner
<b>Project Size</b>	1							
<b>Location</b>	.027	1						
<b>Purpose</b>	-.016	-.048	1					
<b>Cost Underrun</b>	-.013	-.081	.016	1				
<b>Cost Overrun</b>	<b>.28**</b>	-.032	<b>.12**</b>	<b>-.50**</b>	1			
<b>Cost Performance</b>	.017	-.002	-.046	-.040	<b>-.15**</b>	1		
<b>Scope</b>	.13**	-.031	-.003	.016	.031	-.010	1	
<b>Partner</b>	<b>-.327**</b>	<b>-.177**</b>	-.057	-.001	<b>-.33**</b>	<b>.13**</b>	.03	1

\*\* . Correlation is significant at the 0.01 level (2-tailed).

Table 3. Goodness of Fit Tests

Distribution Type	Sig. $\alpha$ Level	Kolmogorov- Smirnov ( $D$ ) Critical Value	Anderson Darling ( $A^2$ ) Critical Value	Chi-squared ( $\chi^2$ ) Critical Value
<i>Cauchy</i> Cost Performance (N=1093)	<b>0.2</b>	0.03246	1.3749	13.442
	<b>0.1</b>	0.03699	1.9286	15.987
	<b>0.05</b>	0.04108	2.5018	18.307
	<b>0.02</b>	0.04592	3.2992	21.161
	<b>0.01</b>	0.04927	3.9074	23.209
<i>Johnson <math>S_B</math></i> Cost Overruns (N=657)	<b>0.2</b>	0.4186	1.3749	N/A
	<b>0.1</b>	0.04771	1.9286	N/A
	<b>0.05</b>	0.05298	2.5018	N/A
	<b>0.02</b>	0.05922	3.2892	N/A
	<b>0.01</b>	0.06355	3.9074	N/A
<i>Wakeby</i> Cost Underruns (N=436)	<b>0.2</b>	0.05139	1.3749	N/A
	<b>0.1</b>	0.05857	1.9286	N/A
	<b>0.05</b>	0.6504	2.5018	N/A
	<b>0.02</b>	0.0727	3.2892	N/A
	<b>0.01</b>	0.07801	3.9074	N/A

Table 4. Example of discrete probabilities for cost overruns/underruns

<b>Final Approved Budget (£ million)</b>	<b>Probability</b>	<b>P(X &lt; X1)</b>	<b>P(X &gt; X1)</b>	<b>P(X1 &lt; X &lt; X2)</b>	<b>P(X &lt; X2)</b>	<b>P(X &gt; X2)</b>
<i>Johnson S<sub>B</sub></i> Cost Overruns (N=657)	1 and 10%	0.07	0.93	0.43	0.51	0.49
	11 and 20%	0.52	0.48	0.13	0.66	0.34
	21 and 30%	0.67	0.33	0.08	0.75	0.25
	31 and 40%	0.76	0.24	0.05	0.82	0.18
	41 and 50%	0.82	0.18	0.04	0.86	0.14
	51 and 60%	0.87	0.13	0.03	0.90	0.10
<i>Wakey</i> Cost Underruns (N=436)	-1 and -10%	0.93	0.07	-	-	-
	-11 and -20%	0.59	0.41	-	-	-
	-21 and -30%	0.40	0.60	-	-	-
	-31 and -40%	0.28	0.72	-	-	-
	-41 and -50%	0.22	0.78	-	-	-
	-51 and -60%	0.18	0.82	-	-	-

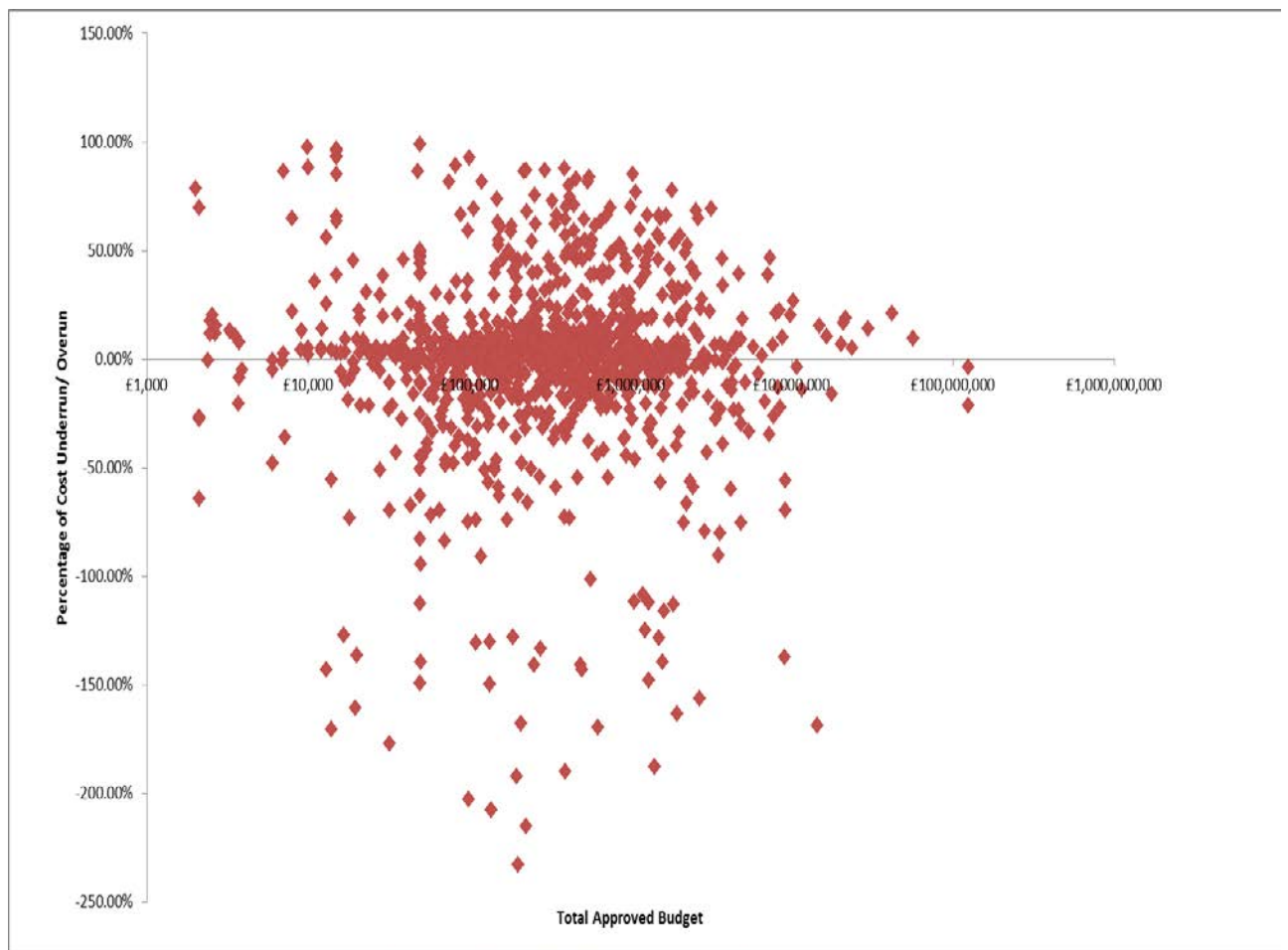


Figure 1. Logarithmic distribution of cost performance

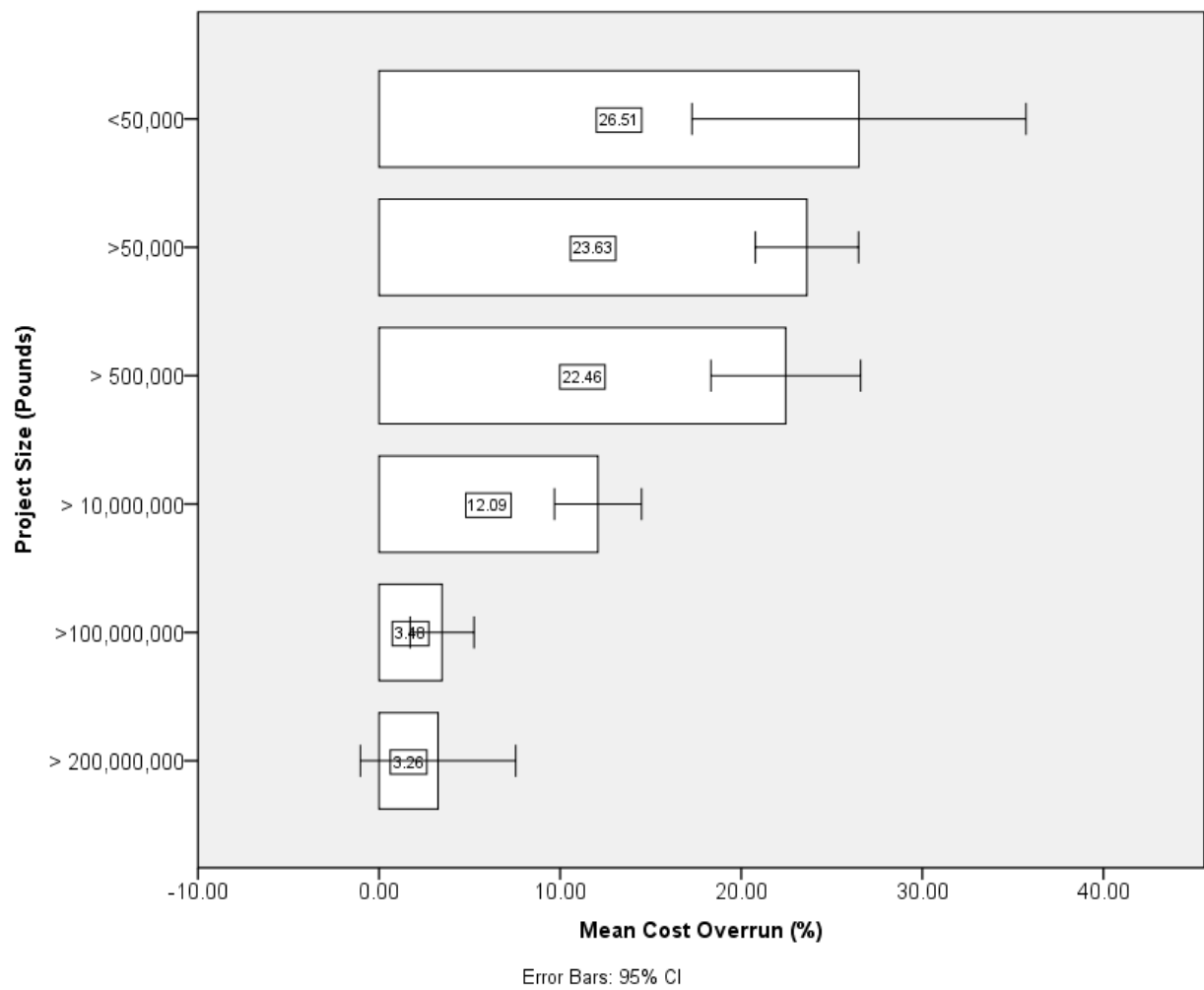
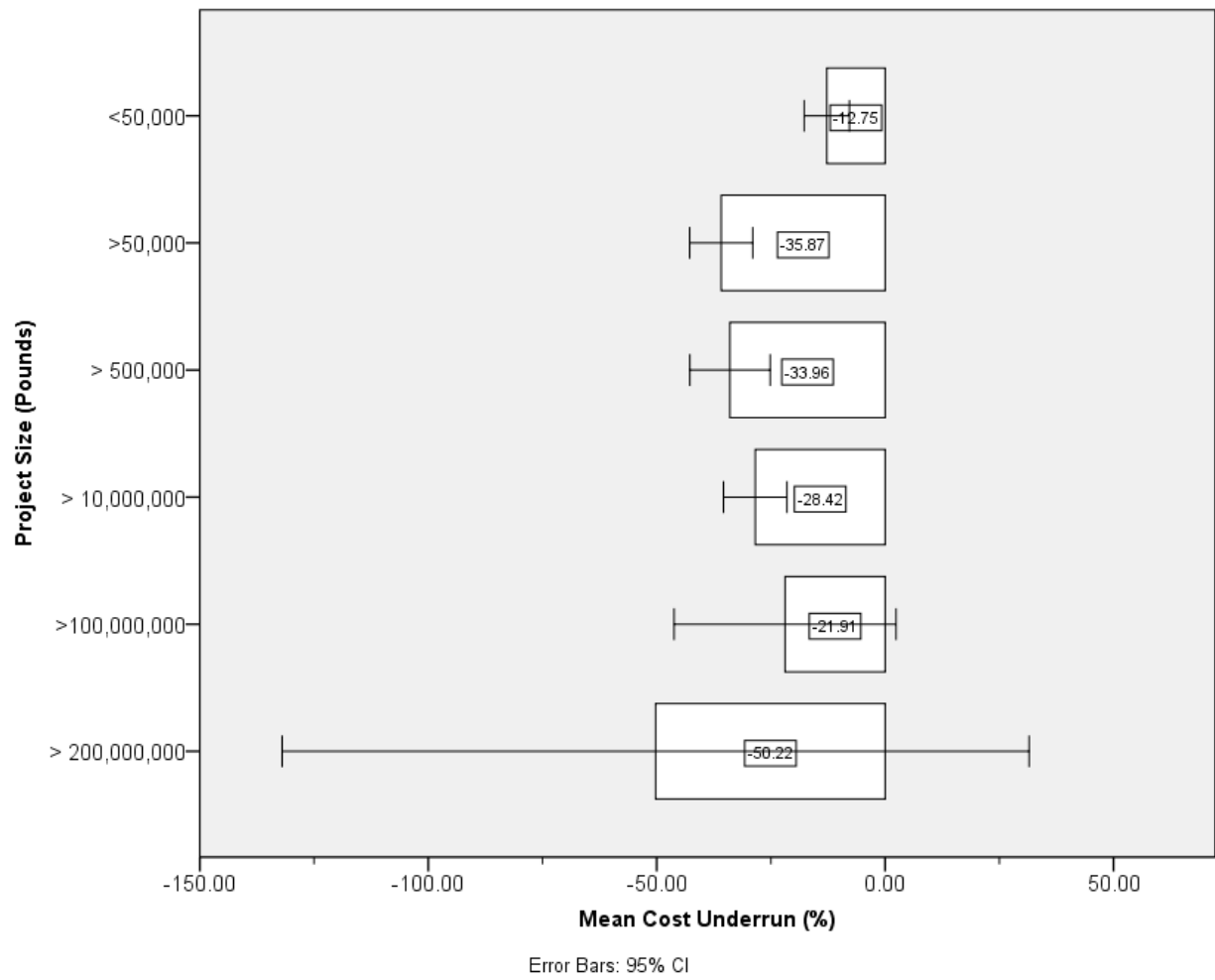


Figure 2. Mean cost overrun for the sampled projects



Figure 3. Mean cost underrun for the sampled projects



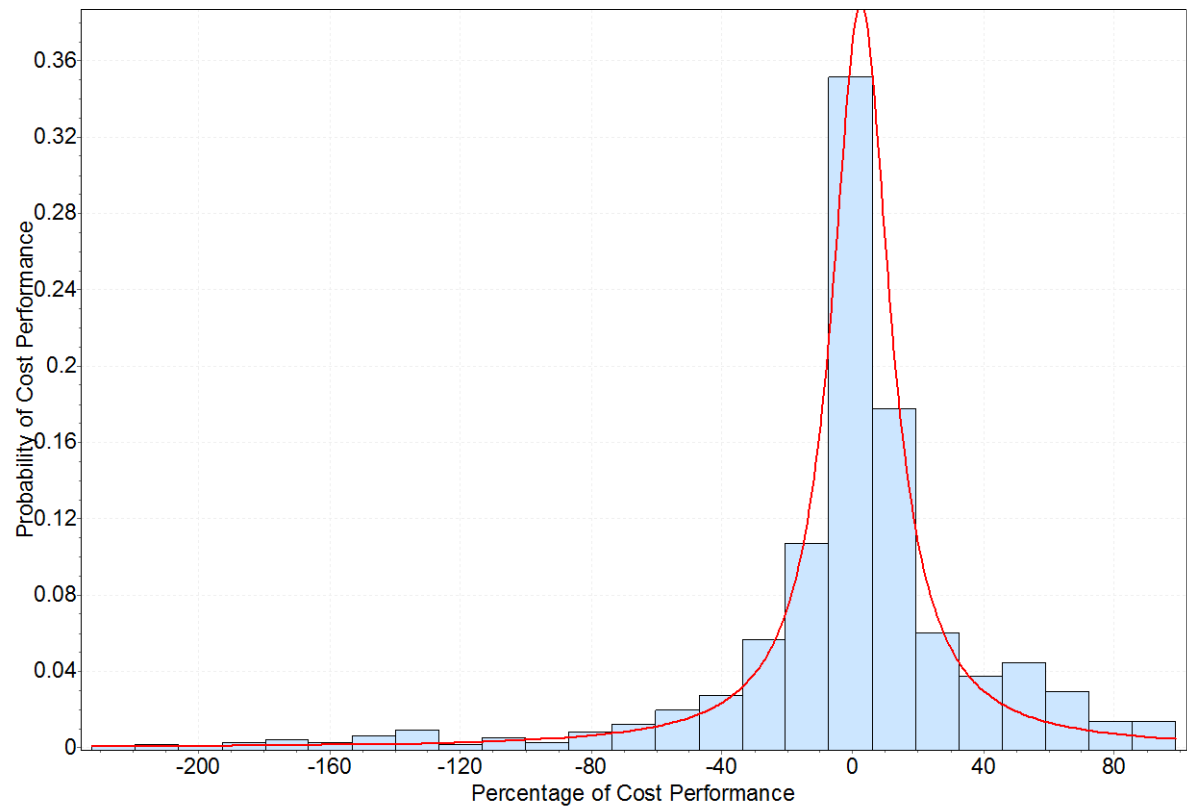


Figure 4. *Cauchy*: PDF for cost performance

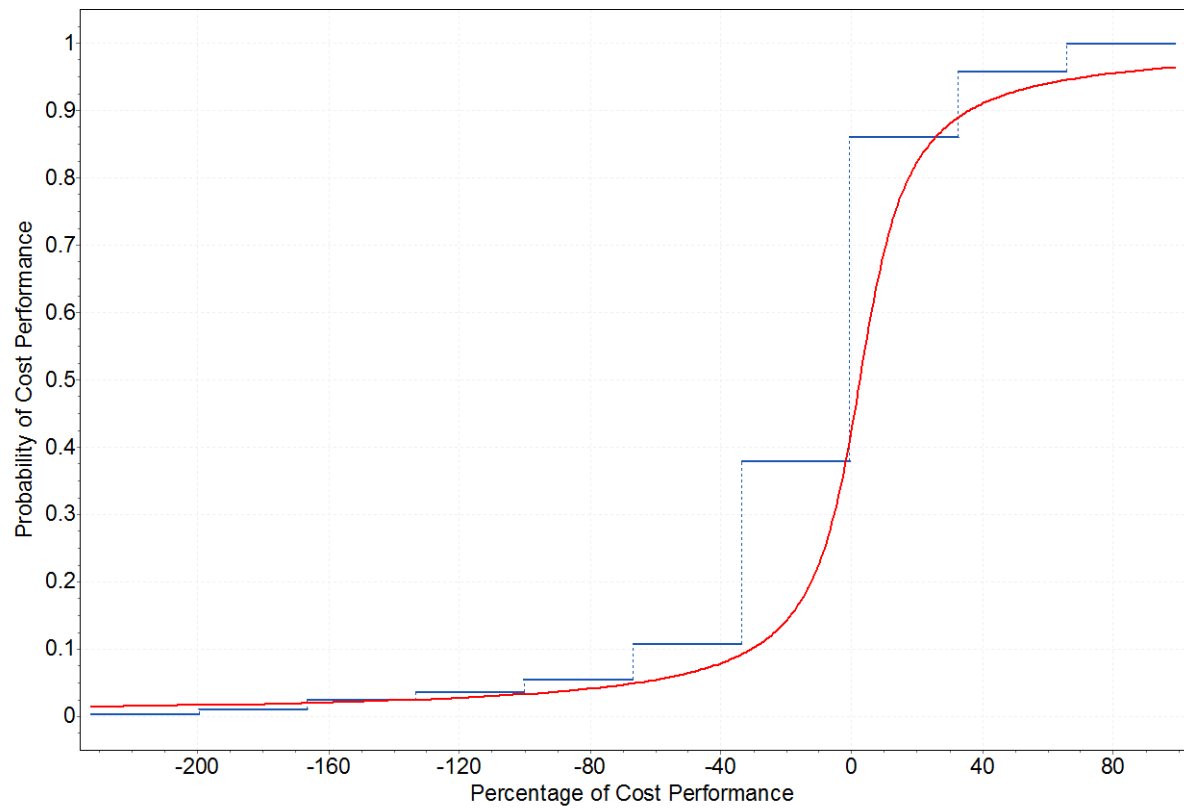


Figure 5. *Cauchy*: CDF for cost performance

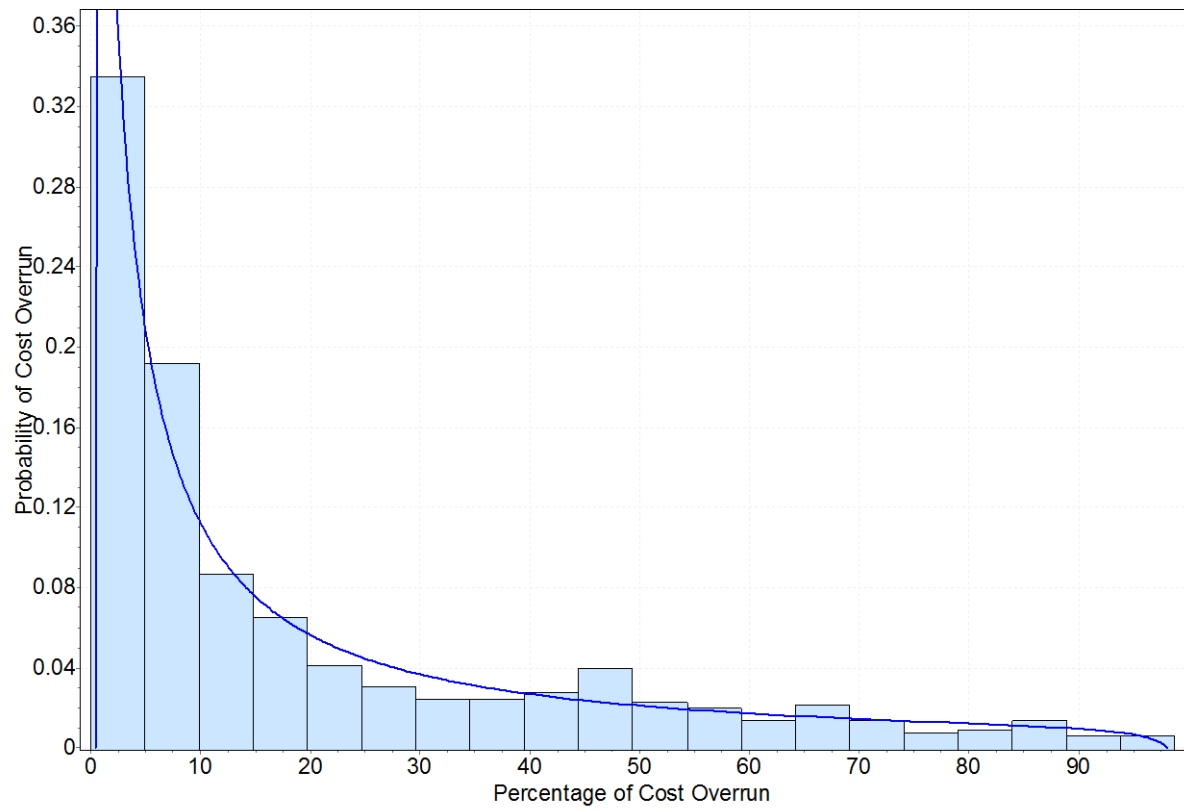


Figure 6. *Johnson  $S_B$* : PDF for cost overruns

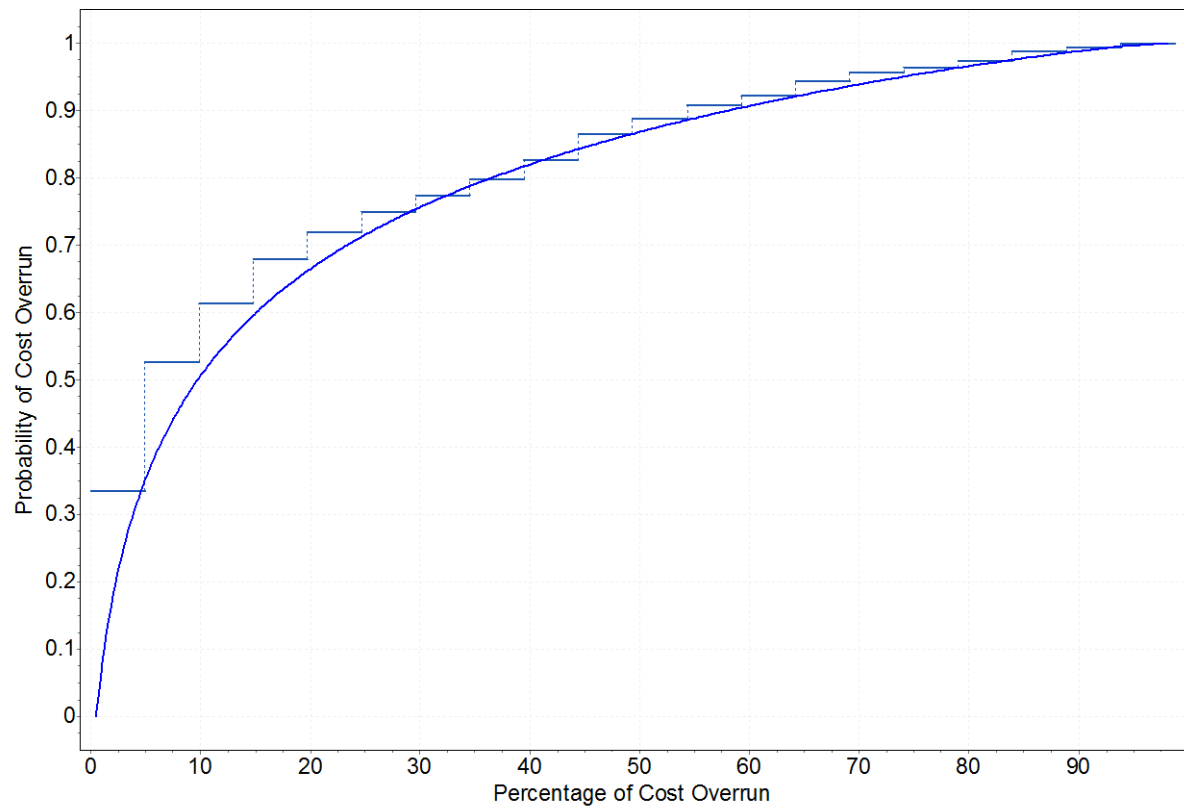


Figure 7. *Johnson  $S_B$* : CDF for cost overruns

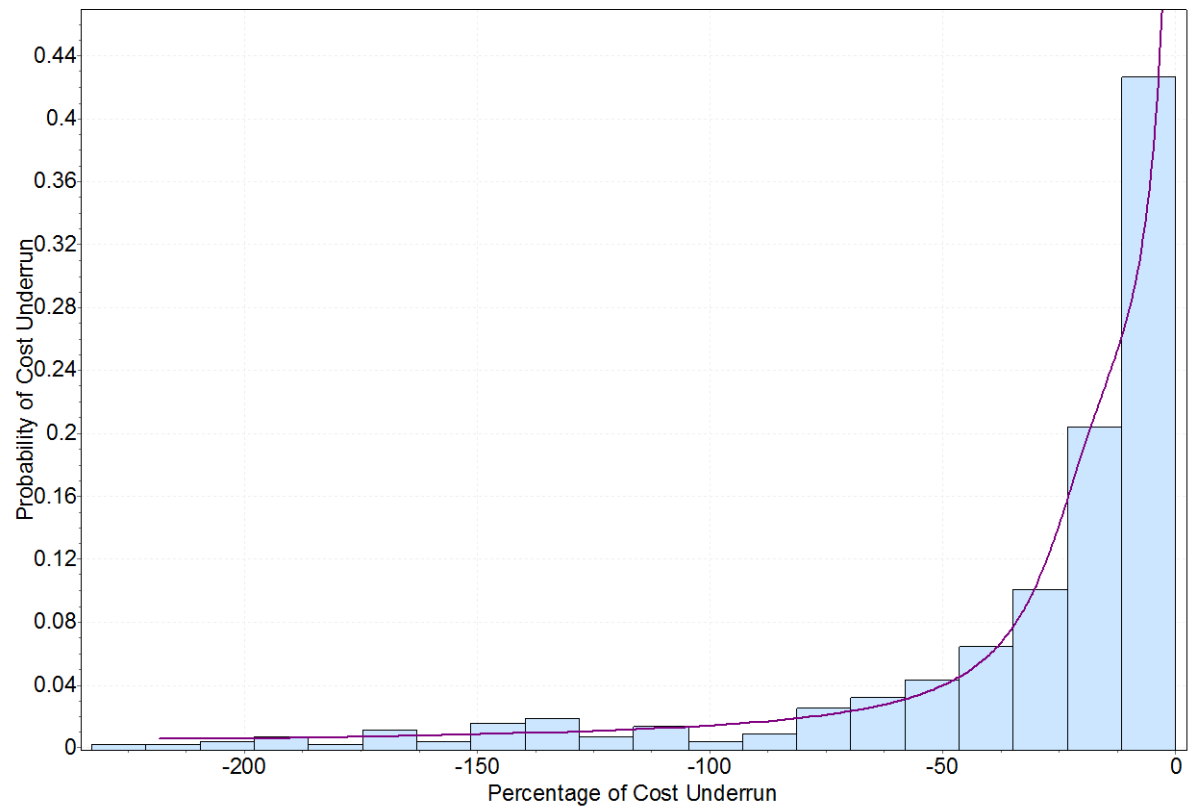


Figure 8. *Wakeby*: PDF for cost underruns

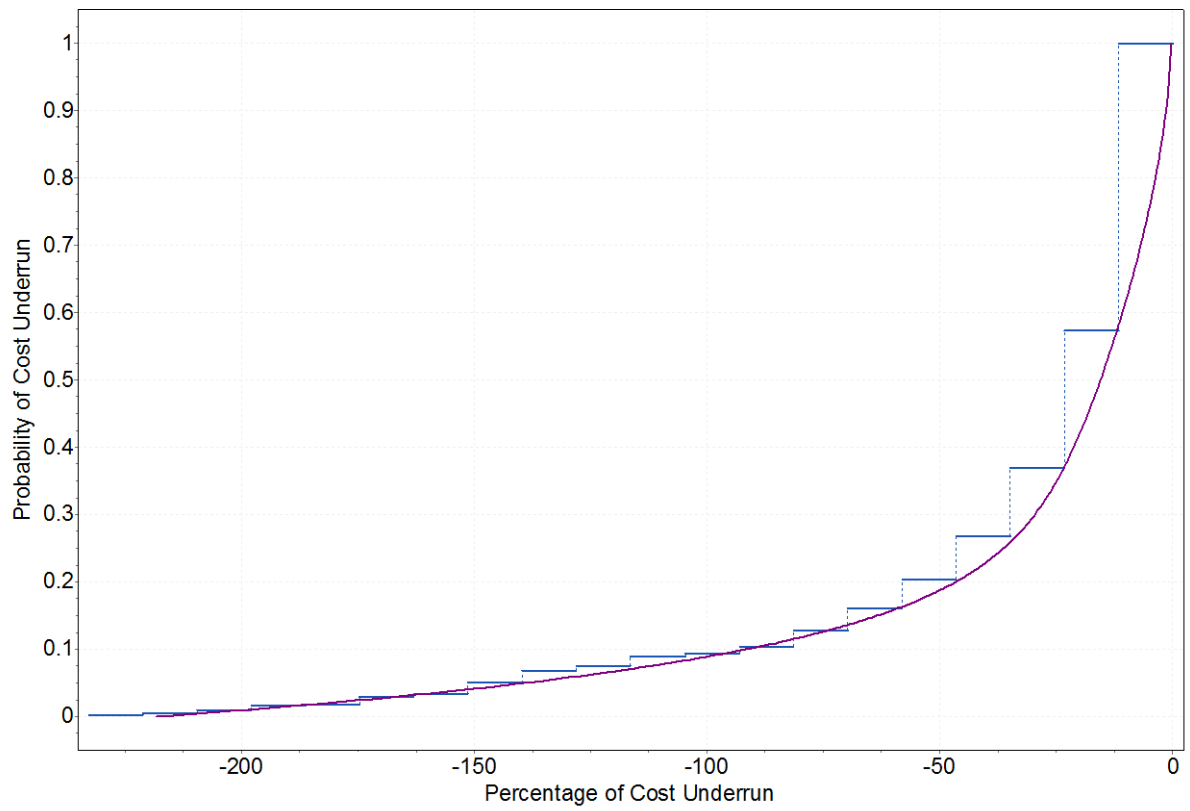


Figure 9. *Wakeby*: CDF for cost underruns